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Explaining water security indicators using hydrologic and agricultural systems models

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ABSTRACT

Water security plays an important role in socio-economic development, ecosystem management, and environmental sustainability. Over the last four decades, water security assessment has attracted much political and economic attention. An improved understanding of the relationships between water demand and supply is needed to mitigate the impacts of diminishing water resources. This study provides an overview of water security assessment by focusing on the various water security indicators and the concept of water footprint (blue, green, and grey water). The water security indicators based on the water footprint concept is currently receiving more attention because it accounts for the return flow from the total water withdrawn from a watershed. We also investigate the application of different physically-based hydrological models, such as Soil and Water Assessment Tool (SWAT) and Variable Infiltration Capacity (VIC), on water security assessment at a regional to continental scale. However, hydrological/agricultural system models cannot quantify evapotranspiration from irrigation and rainwater separately. Therefore, independent quantification of blue and green water footprint from an irrigated field is challenging. For illustration purposes, we apply the fully distributed Agricultural Ecosystems Services (AgES) model in the Big Dry Creek Watershed (BDCW), an intensively managed and irrigated watershed located in semiarid Colorado. The results indicate that the blue water footprint is higher than the green water footprint in the watershed. In addition, the spatial distribution of grey water footprint is highly correlated with the amount of fertilizer application. The variation of grey water footprint among the irrigated fields is higher than blue and green water footprints. We conclude that applying a physically distributed model can provide useful insight into the impact of climate and anthropogenic activities on water security at different scales.

1. Introduction

The shortage of freshwater resources is a daunting reality, and the current manifestation is that two-thirds of the global population lives under severe water scarcity at least one month of a year (Mekonnen and Hoekstra, 2016; He et al., 2021; Stenzel et al., 2021). In addition, the Global Risk Report (World Economic Forum, 2015) identified that the crisis due to water scarcity has the highest impact in the current global situation. Meanwhile, it is anticipated that by 2050, the global population will increase up to 32%, and the corresponding food demand will increase up to 60% (Boretti and Rosa, 2019). Therefore, since the late 1980s, water scarcity research has been identified as one of the key elements for formulating policies at global and regional scales (Liu et al., 2017a,b). The linkage of freshwater shortage with rapidly growing population associated with increasing demand in different water sectors such as agriculture, domestic, and municipal water usage sectors are well documented (Veettil and Mishra, 2016, 2020, 2018; Wada et al., 2017, 2011; Kummu et al., 2010; Oki and Kanae, 2006a,b; Vörösmarty et al., 2000).

The changing pattern of land use and climate variables stresses the hydrologic cycle, thereby affecting local and regional water security (Veettil and Mishra, 2018, 2020; IPCC, 2014; 2021). However, quantifying the effect of climate change on water security is challenging due to the uncertainties associated with climate model projections, particularly for the pattern and magnitude of precipitation (Schewe et al., 2014). In addition, the intensity and characteristics of water scarcity impact due to climate change can vary substantially from region to region, and the magnitude of scarcity is coupled with population growth, expansion of

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agriculture, and industrialization (Abbaspour et al., 2009; Haddeland et al., 2014). Moreover, it is surprisingly challenging to assess whether the water scarcity in a region is related to supply (i.e., available water) or lack of better water demand management among different sectors.

Water security depicts the acceptable level of water-related risk of a water resource while satisfying the need for livelihood, human well-being, economic, and ecosystem functioning (UN, 2013; Rodrigues et al., 2014; Grey and Sadoff, 2007). Water security of a region is addressed by the concepts of water stress, shortage, and scarcity, related to the accessibility of population to the freshwater resources (Veettil and Mishra, 2018, 2020). Here water scarcity depicts the long-term water imbalance between demand and supply (EU, 2007). Formulating water management policies at global, regional, national, and local scales may obfuscate the scenarios of “water scarcity” and “drought” (Pereira et al., 2002). Therefore, understanding the fundamental difference between water scarcity and drought is crucial. A comprehensive overview of drought, including drought classification, propagation, and drought indices from a user perspective, is provided in Mishra and Singh (2010).

Recently, physically distributed hydrological modeling has been widely used to comprehensively evaluate water security at different spatiotemporal scales (Veettil and Mishra, 2018, 2020; Florke et al., 2018; Wada et al., 2017; 2014). Hydrological models such as SWAT (Soil and Water Assessment Tool; Arnold et al., 1998; Srinivasan et al., 1998) and VIC (Variable Infiltration Capacity; Liang et al., 1994; Wood et al., 1997) can be used to predict and design sustainable water management policies concerning the changing climate, land use, and growing population (Ma et al., 2020). In this study, we applied a fully distributed model called the Agricultural Ecosystems Services (AgES) model (Green et al., 2014, 2015; Ascough et al., 2015) to an intensively managed suburban and agricultural watershed located in the semiarid region to quantify different water security indicators. The specific objectives of this study are 1) to provide an overview of water security assessment by focusing on various water security indicators and the concept of blue, green, and grey water footprints; 2) to review the existing hydrological and agricultural system models, which can be applied to quantifying water security indicators; 3) to illustrate the water security assessment based on blue, green, and grey water footprint, by applying a fully distributed Agricultural Ecosystems Service (AgES) model in an intensively managed and highly irrigated watershed in the semiarid Colorado State.

The manuscript is organized as follows: Section 1.1 discusses the concept and need for water security assessment; Section 1.2 discusses the water security indicators; Section 2 discusses the water footprint (WF) concept; Section 3 discusses the sectoral application of water footprint concepts; Section 4 explains the quantification of green and blue water scarcity; Section 5 discusses the role of various hydrological models in water security assessment. The application of AgES and major findings are discussed in subsequent sections.

1.1. Concept and need for water security assessment

In the past, the use of the term “water security” has increased across a wide range of disciplines (Cook and Bakker, 2012). The World Economic Forum (WEF) and UNESCO’s Institute for Water Education prioritized water security as a significant global risk, linking the web of food, energy, climate, and economic growth challenges (Mekonnen and Hoekstra, 2016; Liu et al., 2017a,b; Vörösmarty et al., 2021). In addition to rapid population growth, diets in society are shifting toward more livestock-based products (Schyns et al., 2019, 2015; Molden, 2007), and the water footprints related to such products are substantial (Erb et al., 2009; Odegard and van der Voet, 2014).

The Sustainable Development Goals (SDGs) aim to develop across multiple sectors, such as clean energy, zero hunger, no poverty, and Clean Water and Sanitation. Water security is essential to meet most SDGs by 2030 (UNESCO, 2019). However, recent studies indicate that water security’s importance has been highly underestimated (Vörösmarty et al., 2018). Therefore, SDGs context requires significant worldwide involvement to redirect the current downward trajectory in water security goals. In addition, the climate projections-based analysis suggests less reliable freshwater in the 21st century than in the 20th century, with observations that wet regions become wetter and dry regions become drier (Kumar et al., 2014), leading to increasingly vulnerable water security in dry regions. In addition, the policies for energy production from biomass create stress on water resources (Hejazi et al., 2014). According to Stenzel et al. (2021), the additional water withdrawal for bioenergy crop irrigation may create more water stress. The population living under severe water stress would double compared to today because of the additional water withdrawal and even exceed the impact of climate change. Therefore, future water availability and use studies need to include the possibility of new high demands for water from a growing bioenergy sector.

The excessive loading of pollutants into water bodies is another important factor that threatens water security (Van Vliet et al., 2017; Mishra et al., 2021). Urbanization, untreated water from industries and households, and nonpoint sources of pollution from agricultural fields contribute toward water quality deterioration, mostly in developing countries; as a result, water scarcity is considerably changed in many regions (Van Vliet et al., 2017; Mishra et al., 2021). However, most analyses of global water security are focused on the water quantity aspects, whereas the water usage in each sector depends on water quality. For example, salinity and nutrients are major concerns in irrigated agriculture, and water temperature is important in the thermoelectric power sector. Therefore, it is crucial to consider both water quantity and quality while performing water scarcity analyses. Monitoring water quality in stream channels and addressing its impact on water security is still a major issue. Evaluation of grey water indices for nutrient discharge zones can indicate the degree of water quality degradation of a stream (Aldaya et al., 2020; Liu et al., 2017a,b; Wu et al., 2012). Therefore, expanding water monitoring gauges in the global river network is essential to achieving this goal (Mishra and Coulibaly, 2010). However, water quality models are being developed to provide relevant water quality information, particularly in data-scarce regions (UNEP, 2016; Harmel et al., 2006).

The impact of climate change on water security is a fundamental concern (He et al., 2021; Dolan et al., 2021) that causes more extreme floods and droughts globally (Konapala et al., 2020). The water management practices in many regions are not adequately designed to handle the impacts of climate change on the reliability of water supply, flood and drought risk, agriculture, energy, and ecosystems. Moreover, the land area subject to severe water scarcity is likely to be more than double that in the present (Trnka et al., 2019), and a rigorous regional prediction of water supply trends is substantially more complicated than analyzing the global picture.

Water scarcity may lead to devastating consequences such as eradicating aquatic systems, extinction of species, water-borne diseases, and growing regional and international risks of conflicts related to water sharing (Di Baldassarre et al., 2019; Gleick, 1998). Therefore, regional and global planning of water allocation in different sectors are necessary to address the following concerns: (i) the amount (percentage) of water that can be used by a population from a particular water resource; (ii) criteria for farmers to access a water resource; (iii) the amount of water required to maintain the environmental flow with acceptable quality; and (iv) the percentage of water we should leave for future use. However, long-term water planning and technological investments (e.g., massive infrastructure) are critical for sustainable and improved water security (Gleick, 2003, Vörösmarty et al., 2010). Although natural and artificial reservoirs/structures help increase regional renewable freshwater resources, maintaining an environmental flow is vital for ecological health (Oki and Kanae, 2006a,b; Vanham et al., 2018). Based on monthly water scarcity analysis, Hoekstra et al. (2012) observed that most river basins worldwide are going through low, moderate, or significant water scarcity for at least one month of a given year. Therefore, water security assessment by considering water availability, supply, and demand is necessary for stakeholders to develop appropriate policies for improving water management in a changing environment.

1.2. Water security indicators

Since the 1980s, many water security indicators have been developed to evaluate the status of freshwater accessibility (Liu et al., 2017a, b; Srinivasan et al., 2017; Pedro-Monzonís et al., 2015; Brown and Matlock, 2011; Rijsberman, 2006; Seckler et al., 1999; Falkenmark, 1989). These indicators may also explain and mitigate long-term water supply challenges, socioeconomic status, and environmental risks. Also, these indices are primary measurement tools for assessing the water scarcity of a region or a sector (e.g., economic, social, or ecological). Table 1 presents the most widely employed water security indices among more than 150 indices identified (Damkjaer and Taylor, 2017).

Typically, a water security indicator is quantified based on water availability, consumption, population, water usage in different sectors, and environmental flow requirement (EFR). Water security indicators, which received significant global attention, were derived during the late 1980s (Nouri et al., 2019; Liu et al., 2017a,b) have been used to analyze population-driven water stress on the global freshwater resources (Srinivasan et al., 2017; Falkenmark, 2013). For instance, the Falkenmark Index (FLK; Falkenmark, 1989), the fraction of total runoff (streamflow) available for human use evaluates the volume of freshwater per capita share (m^3/person/year), is the most widely employed water security indicator for representing differences in water availability between countries (Karabulut et al., 2016; Damkjaer and Taylor, 2017; Pedro-Monzonís et al., 2015; Brown and Matlock, 2011).

Based on the per capita water usage, the Falkenmark index of a region is categorized as no stress (FLK > 1700 m^3/person/year), stress, scarcity, or absolute scarcity (FLK < 500 m^3/person/year). This index clearly distinguishes between climate and human-induced water scarcity (Vörösmarty et al., 2005). However, FLK omits major variations in water demand among countries due to culture, lifestyle, and climate (Rijsberman, 2006). Also, the index does not reflect the transparent spatial distribution of domestic, industrial, and agricultural water demand distinctly (Schewe et al., 2014). OhIsson (2000) modified FLK by incorporating the influence of industrial, economic, or other sectors on water demand and formulated the Social Water Stress Index (SWSI).

The ratio of water use to availability is a widely accepted water scarcity indicator, which addresses the volume of water used and connects it to the available freshwater resources (Alcamo and Henrichs, 2002; Liu et al., 2017a,b). Here, water use refers to the total volume of water withdrawal by different sectors (consumptive use), and the available water can be an actual runoff or actual runoff minus EFR (Environmental Flow Requirement). The measurements focused on the 'withdrawals' ignore the return flows after consumptive use and thus do not provide a comprehensive picture of water scarcity over a watershed (Veettil and Mishra, 2016). For instance, in most thermoelectric power plants, less than three to five percent of water withdrawn is consumed through evaporation, whereas 85% of total water use is considered 'consumption' in the irrigation sector. Therefore, in water security assessment, we need to consider the consumptive water use (net water abstraction) rather than water withdrawal because return flows can often be reused and thus do not necessarily contribute to water scarcity. Researchers have developed many physically-based models that address spatiotemporal changes in sectoral water demand and availability. Since the early 2000s, water security analysis based on the water footprint concept (Hoekstra et al., 2011) that includes blue, green, and grey water footprints are considered appropriate for addressing water security at regional to global scale.

Table 1
Water security indicators.

Indices	Input variables/ methodology	Water Quantity	Water Quality	Reference
Falkenmark Indicator	Water availability, Population	✓		Falkenmark et al. (1989)
Basic Human Water Requirements	Water availability for basic human needs	✓		Gleick (1996)
IWMI indicator (Physical and Economical Water Scarcity)	Calculated based on existing water infrastructure of a river basin	✓		Seckler et al. (1999)
Social Water Stress Index	Measure the economic, technological, and other sectors impact on water	✓		OhIsson (2000)
Water Poverty Index	Consider water availability, access to freshwater, time taken to collect fresh water for domestic use	✓		Sullivan (2002)
Local Relative Water Use and Reuse	Domestic, industrial, and agricultural water use	✓		Vorosmarty, et al. (2005)
Water Stress Indicator	Calculated based on mean annual runoff, withdrawal, and EFR	✓		Smakhtin et al. (2005)
Watershed Sustainability Index	Incorporates hydrology, environment, life, and policy	✓		Chavez and Alipaz (2007)
Water Supply Stress Index	Calculated based on water demand and water supply of a river basin	✓		McNulty et al. (2010)
LCA-based Water Scarcity Index	Consider human health, ecosystem quality, and resources	✓	✓	Pfister et al. (2009)
Fresh Water Provision Indicator	Calculated based on EFR, water quality	✓	✓	Logsdon and Chaubey (2013)
Water Footprint based indices				
Blue water scarcity	Calculated based on blue water footprint, blue water availability, and EFR	✓		Hoekstra et al. (2011)
Green water scarcity	Calculated based on green water footprint, soil water storage (green water storage)	✓		Hoekstra et al. (2011)
Water Pollution Level	Calculated based on water pollution and streamflow		✓	Hoekstra et al. (2011)
Blue water vulnerability	Blue water scarcity during low flow/ drought	✓		Rodrigues et al. (2014)
Green water vulnerability	Green water scarcity during low flow/drought	✓		Rodrigues et al. (2014)

2. The water footprint concept

The water footprint (WF) concept developed by Hoekstra (2003) was initiated to develop a suitable indicator to evaluate increasing human consumption of freshwater resources and to address the rising opportunity cost of freshwater use in different sectors (Chenoweth et al., 2014). WF is a multidimensional indicator capable of calculating water consumption for (i) a person, (ii) growing populations, (iii) a process, (iv) a product, (v) a river basin, or (vi) a nation. The WF is classified into blue, green, and grey water (Fig. 1). Additionally, quantifying

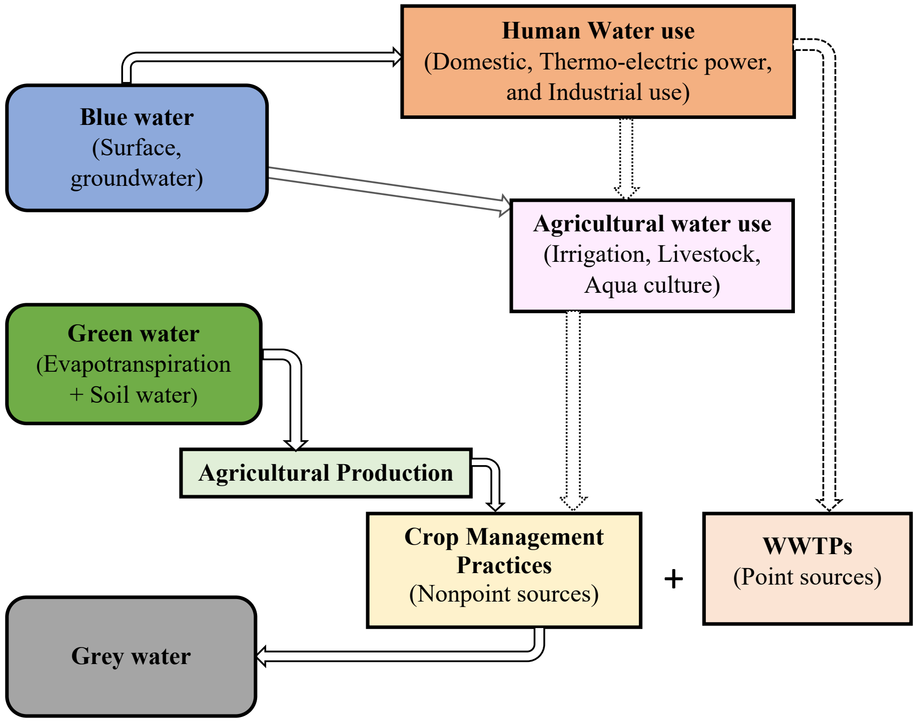

Fig. 1. Conceptual diagram of water footprint concept based on different applications.

consumptive water use will provide a more accurate assessment of the amount of water required for production and better determine the water security hotspot (Marston et al., 2018; Konar and Marston, 2020). A comprehensive explanation of the WF concept and classification is provided in the following sections.

2.1. Blue and green water footprint

Precipitation falling on a landscape is partitioned into different components such as evapotranspiration, soil moisture, and runoff. Traditional water resources planning and management focus on the efficiency and economics of water storage and diversion of runoff (Hoekstra, 2019a,b), but this approach fails to efficiently allocate the evaporative component (Hoekstra, 2019a,b; Schyns et al., 2019). Addressing water security issues and identifying source areas by classifying freshwater resources based on “color” is an appropriate method for proper water management (Chenoweth et al., 2014; Schneider, 2013). In addition, this concept links the depletion of water resources and increasing population needs. Here, blue water refers to the total volume of surface and subsurface water, stored in lakes, aquifers, and manmade structures and accessible for human consumption (Falkenmark and Rockström, 2010; Rockström et al., 2009; Rodrigues et al., 2014; Hoekstra et al., 2011). Blue water footprint (WF_b) is the consumptive water use from blue water resources that can be calculated as the volume of surface/groundwater consumed for the production of goods (e.g., power production, irrigation) or service (e.g., domestic water use, public water use). More systematically, the WF_b in a watershed is the difference between water withdrawal (abstraction) and returned flow (Hoekstra et al., 2011; Chapagain and Tickner, 2012).

Broadly, green water is defined as the soil water stored in the vadose zone and vegetation canopy, derived from the precipitation and available to the plant roots and soil biota (Rockström et al., 2009; Rost et al., 2008; Veettil and Mishra, 2016, 2020). Green water footprint (WF_g) indicates the volume of rainwater consumed during the production process and is relevant for agricultural and forestry products (Hoekstra, 2019a,b; Hoekstra et al., 2011). Roughly, in a continental scale, 65% of precipitation produces green water and the remaining 35% forms blue water (Falkenmark and Rockström, 2010), and it is evident that 67% of the global crop system still comes from rainfed agriculture (Portmann et al., 2010), where the water consumption purely depends on green water. Moreover, 80% of the global green water footprint is associated with global agricultural production (Liu et al., 2009), which incorporates animal products, food crops, and bioenergy crops (Mekonnen and Hoekstra, 2012a,b, 2011).

However, the importance of distinctly quantifying the blue and green water footprints requires further research to use them precisely and explicitly (Hoekstra, 2019a,b); (Mekonnen and Hoekstra, 2020). Falkenmark and Rockstrum (2006) differentiated green water into two components: (i) Green water storage, which refers to the total moisture in the soil. (ii) Green water flow, which indicates the actual evaporation (non-productive part) and actual transpiration (productive part) (Link et al., 2021; Veettil and Mishra, 2016). A few research considers this productive part as green water flux (Rost et al., 2008). Further, the concept is indistinct whether it represents evapotranspiration (ET) only from rainwater stored in the soil or includes irrigation or other blue water sources (Hoekstra, 2019a,b). In addition, the blue and green water terms are used to define water use instead of total water resource availability (e.g., Chenoweth et al., 2014). Therefore, all these obscurities may result in avoiding the usage or application of the blue and green water concept in the hydrological communities (Hoekstra, 2019a, b).

2.2. Grey water footprint

Grey water footprint (WF_y) indicates the potential water quality impairment caused by the production of good or service, and it is defined as the amount of dilution water (freshwater) required to assimilate the concentration of nutrients/chemicals to approximate the natural (original) concentration of a given stream (Aldaya et al., 2020; Hoekstra et al., 2012; Wu et al., 2012, 2021). In general, the water quality assessment for a river basin is performed based on the flow of nutrients/pollutants released from agricultural fields (nitrogen, phosphorus, potassium, and lime) as well as the effluent flow from wastewater treatment facilities (Yan et al., 2021; Humbird et al., 2011). Here

WF_y serves as an index for investigating the water quality standard of available water in that river basin. This index is calculated as the ratio of nutrient load to the allowable nutrient load in the region. For instance, in the case of nitrate (NO_3) load,

$$WF_y = \frac{L_{NO3}}{NO3_{max} - C_{NO3}} \tag{1}$$

where L_{NO3} is the nitrate loading (in mass/time) in water bodies as a result of nitrogen inputs (e.g., fertilizer application, WWTP inflow); $NO3_{max}$ is the maximum allowable nitrate concentration in ambient water quality standards. The value set by the EPA is 0.01 kg/m^3 for human consumption; C_{NO3} is the natural nitrate concentration in the stream network.

Nitrate is identified as the largest component in grey water because its loading far exceeds other nutrients in general (Wu et al., 2012, 2021; Aldaya et al., 2020). However, the scientific validity of WF_y concept has been criticized. For instance, Gawel and Bernsen (2011) stated that grey water is fictional or a theoretical concept that does not reflect the opportunity cost associated with production and consumptive use. In addition, accurate measurement of the background pollutant concentration of streams is challenging. The allowable concentration value is not formulated for most nutrients and regions (Chenoweth et al., 2014). Moreover, the blue and green water footprint illustrates the pressure on water resources, while grey water is an environmental impact indicator.

3. Sectoral application of water footprint concept

The application of the WF concept is rapidly increasing in most sectors (e.g., food production, energy projects, and industry). These analyses are performed on a regional or river basin scale to a continental or global scale. A WF assessment aims to evaluate how human actions contribute to blue and green water scarcity and pollution (grey water) issues. The assessment helps quantify the impact of WF on the environmental, social, and economic sectors and frame a strategy for solving the pressure on water resources. According to the Food and Agricultural Organization, the WF concept can produce beneficial means of evaluating virtual water flow through the trade of food and other commodities (Dalin et al. 2019; Hoekstra, 2019a) and of generating public awareness on global water usage and related water scarcity. In this section, we provide an overview of the application of WF concept in different sectors such as food production, biofuel production, and some other sectors, including industry, mining, and energy production.

3.1. Food production sector

The water footprint of major food crops has been analyzed to provide a clear picture of freshwater consumption during the production process (Hoekstra, 2017; Lovarelli et al., 2016). For example, Mekonnen and Hoekstra (2011) quantified global crop production's green, blue, and grey WF using the CROPWAT model. Globally, the total volume of WF estimated for 126 crops was 7404 billion cubic meters per year with 78% green, 12% blue, and 10% grey WF. For example, WF for wheat was 1827 m^3/ton (WF_g of 1277 m^3/ton, a WF_b of 342 m^3/ton, and a WF_y of 207 m^3/ton). In addition, the WF of major crops (e.g., rice) varies significantly from region to region (Chapagain and Hoekstra, 2011; Zhuo et al., 2016). Significant rice production is observed in South Asian countries, where cultivation is mainly carried out in the wet season. Therefore, the contribution of blue water scarcity is negligible in those areas.

The water footprint of animal products is relatively higher than the crop products with equivalent nutritional value (Mekonnen and Hoekstra, 2012a,b; Hoekstra, 2017). For example, beef's average WF per calorie is 20 times larger than cereals and starchy roots, and WF per gram of protein for milk, eggs, and chicken meat is 1.5 times larger than for pulses. In general, industrial livestock products consume and pollute more blue water resources than the products from grazing systems. Global animal production requires about 2,422 Gm^3 of water per year, of which 87.2% is WF_g, 6.2% is WF_b, and 6.6% is WF_y (Mekonnen and Hoekstra, 2012a,b). Therefore, the rising global meat consumption and the intensification of animal production systems will further pressure the global freshwater resources in the impending decades (Zhuo et al., 2016). The WF analysis for various food crops and animal products is provided in Table 2a.

3.2. Biofuel/energy production sector

Anthropogenic greenhouse gas (GHG)emission has been the most significant contributor to climate change since the mid-20th century, and the majority is from the energy and transportation sectors (Scown et al., 2011; Mbow et al., 2017). Many researchers have found the use of biofuels, such as ethanol and biodiesel, will strongly support the reduction of GHG emissions (Mahbub et al., 2019; Kongboon and Sampattagul, 2012). For example, the US Department of Energy aims to provide 16% of electricity through biofuel production by 2030 (Gerbens-Leenes et al., 2012). The European Council is encouraging the use of biofuels to increase by 50% by the next decade. Therefore, assessing the WF and related water security analysis due to the biofuel production is necessary for understanding the pressure on water resources (Schyns et al., 2019; Mathioudakis et al., 2017; Dalla Marta et al., 2012).

The biofuel WF varies from crop to crop and region to region depending on the climate, topography, type of crop, and crop yield (Huang et al., 2021; Dalla Marta et al., 2012). For example, biodiesel, generally produced from coconut, groundnut, and cotton, has a relatively high WF (Gerbens-Leenes et al., 2008). In addition, the WFs of sugar cane and cassava vary considerably with respect to the region, climate, and production systems. On average, the WF of sugarcane is less than that of cassava (Kongboon and Sampattagul, 2012). Mathioudakis et al. (2017) estimated the WF of ten crop residue types and a few bioenergy feedstocks, such as miscanthus, eucalyptus, and pine, and revealed that crop residues have a smaller WF than miscanthus and wood. The higher energy use combined with an increasing contribution of energy from biomass will cause competition of water consumption with food production. The application of WF concept in various bioenergy crops is listed in Table 2b. A comprehensive WF assessment of humanity is only possible through comparative analysis of all water usage sectors related to human water use. Table 2c illustrates the application of the water footprint concept in important sectors such as electricity production and mining.

4. Green and blue water scarcity

High-resolution indices are essential for addressing water security at a reliable level. Quantifying water scarcity as a ratio of water consumed (water footprint) to water available is a globally accepted metric (Wada et al., 2011; Rodrigues et al., 2014) that can identify the geographic hotspot for water stress regions. According to Schyns et al. (2019), green water scarcity (*GW_Scarcity*) indicates the competition for limited green water flow, which is involved in the production of biomass that adds to the economy. The *GW_Scarcity* can be quantified as the ratio of WF_g to green water storage. For example, *GW_Scarcity* from a field 'x' and period 't' is calculated as:

$$GW\_Scarcity(x,t) = \frac{GreenWaterFootprint(x,t)}{GreenWaterStorage(x,t)} \tag{2}$$

Here the green water footprint accounts for the consumptive use of vegetation only from precipitation (i.e., not considering the irrigation water). Although green water availability is limited, and there are competing demands in crop production, livestock grazing lands, and forest ecosystems, *GW_Scarcity* has not attracted much attention in water security assessment (Schyns et al., 2019; Link et al., 2021; Vörösmarty

Table 2
Application of water footprint concept to different sectors: a) food production; b) energy and fuel; c) other sectors.

a) Food Production

Field of application	Authors	Major contribution
Crops and crop derived products	(Mekonnen and Hoekstra, 2011)	The water footprint of 126 crops and 200 crop products, including flours, beverages, fibers, and biofuels, on a global scale is quantified.
Wheat	(Mekonnen and Hoekstra, 2010)	The total water consumption for wheat production is quantified, where 55% of virtual water flow was from the USA, Canada, and Australia.
Animals and Animal products	(Mekonnen and Hoekstra, 2010)	The blue, green, grey water footprint of different categories of animals and animal products showed a maximum in beef cattle and cow milk production.
Agricultural consumption	(Rost et al., 2008)	The dynamic global vegetation and water balance model (LPJ) is used for estimating global crop water consumption. The water footprint is significant in irrigated areas, and the alteration of land cover reduced the global evapotranspiration by 2.8% from 1971 to 2000.
Food Aid	(Jackson et al., 2015)	The water footprint for food supply during the emergency for a longer-term (food aid) was 10 km^3 for the year 2005, and the larger donor was the USA.
Rice (Global Scale)	(Chapagain and Hoekstra, 2011)	The global water footprint of rice production is 784 km^3/year, with maximum green water consumption. The study also estimated the ratio of green to blue water for different countries in rice production.
Rice (National scale)	(Yoo et al., 2014)	The national water footprint of Korea in rice production was 844.5 m^3/ton, and they also accounted for the virtual water trade of the countries which import rice to the nation.
Coffee and Tea	(Chapagain and Hoekstra, 2007)	Evaluated the global water footprint of tea and coffee consumption in Dutch society. The calculation is based on water requirements in the major countries exporting the product.
Maize	(Nana et al., 2014)	PolyCrop- multiyear daily crop model is used for calculating the water use according to the simulated growth of maize.
Olives and Olive oil	(Salmoral Portillo et al., 2011)	The green water footprint represented the majority of Spanish olive oil production.
Crop virtual water trade	(Hoekstra and Hung, 2002)	Assessed the crop-related virtual water trade between the nations. The calculated average was 69507 m^3/year for 1995 – 1999.
Wine industry	(Ayuda et al., 2020)	Examined the growth of the blue water footprint of the Spanish wine industry and its increasing environmental impact.
Poultry	(Tsolakis et al., 2018)	The study evaluated the blue water footprint in the poultry supply chain.

b) Energy and Fuel

Bioenergy	(Gerbens-Leenes et al., 2009)	The study analyzed the water footprint of bioenergy from the crops, including Jatropha, which has a maximum production percentage on a global scale.
Bioenergy	(Mathioudakis et al., 2017)	Calculated the water footprint of ten crop residue types and bioenergy feedstocks, such as miscanthus, eucalyptus, and pine.
Biomass	(Gerbens-Leenes et al., 2009)	The water footprint of primary energy carriers derived from biomass in different countries is evaluated. The estimated water footprint of bioenergy was much larger than fossil energy.
Biofuel	(Wu et al., 2012)	The spatial variation of the water footprint of stover ethanol production is estimated based on standardized water footprint methodology combined with hydrologic modeling.
US transportation fuels	(Scown et al., 2011)	Explained the potential change in water footprint due to biofuel and electricity production. The study proved that the production of ethanol and petroleum fuels already impacted aquifer storage due to over-pumping.
Bioethanol	(Dalla Marta et al., 2012)	This study quantified the pressure on water resources due to biofuel production and how it is affected by climate variability.
Bioethanol	(Chiu and Wu, 2012)	This study analyzed the county-level water footprint of bioethanol from corn grain, stover, wheat straw.
Sugarcane and Cassava	(Kongboon and Sampattagul, 2012)	The water footprint of both crops varies considerably with respect to the region, climate, and agricultural production system. On average, the water footprint of sugarcane is less than that of cassava.
Sweeteners and Bioethanol	(Gerbens-Leenes et al., 2012)	Evaluated the WF of sweeteners and bioethanol from sugarcane, sugar beet, and maize.

c) Other sectors

Copper production	(Peña and Huijbregts, 2014)	The study from Northern Chile on extraction and production of high-grade copper found that seawater use will reduce the blue water footprint by 62% in Copper mines.
Electricity	(Mekonnen and Hoekstra, 2011)	The water evaporated from 35 reservoirs to produce electricity was equivalent to the 10% global blue water footprint of crop production in 2000.
Business	(Gerbens-Leenes et al., 2008)	The total volume of water directly or indirectly invested in the business is Business Water Footprint (BWF). Formed an accounting method for BWF, which helps identify all the questions related to water footprint in business performance.
Platinum mine	(Haggard et al., 2013)	WaterMiner tool (program) is used for calculating the water footprint of platinum mines in South Africa.
Industry	(Hoekstra, 2015)	This study discussed a new perspective on the water footprint concept in increasing water use in the industrial sector.
Brick manufacturing	(Skouteris et al., 2018)	The total water footprint of a brick is 2.02 L, of which blue water contribution is relatively higher than green and grey water footprint.
Textile industry	(Li et al., 2017)	Changes in the water footprint of the textile industry from 2001 to 2014 were calculated and compared with the economic growth of the textile industry in China.

et al., 2010; Wada et al., 2011). The evaluation of *GW_Scarcity* assists in addressing a nation's capability to produce enough food, bioenergy, and forestry products with limited blue water availability. Therefore, like blue water scarcity (*BW_scarcity)*, it is critical to consider the *GW_scarcity* and evaluate it through improved modeling approaches.

Environmental Flow Requirement (EFR): Excessive utilization of blue water from a stream may damage the ecosystem health; therefore, application of the EFR concept is mandatory for maintaining a healthy river ecosystem (Honrado et al., 2013). Hirji and Davis (2009) defined the EFR as a standard, which maintains the functions, processes, and resilience of aquatic ecosystems with a minimum quality, quantity, and timing of water flow. Therefore, EFR has a significant role in quantifying the accurate level of blue water scarcity of a region. Although different methodologies (e.g., low streamflow method, Adapted Smakhtin methodology) are developed to evaluate EFR, the presumptive standard method developed by Richter (2010), Richter et al. (2012) is widely used (Liang et al., 2021; Veettil and Mishra, 2018; Zeng et al., 2012). According to the presumptive standard method, water withdrawal from streamflow greater than 20% will cause degradation in ecosystem health, and this available water for withdrawal is termed blue water availability (Veettil and Mishra, 2016). Considering the role of blue water scarcity, the United Nations has identified EFR as one of the Sustainable Development Goals (SDGs), particularly SDG indicator 6.4.2 (Vanham et al., 2018). EFR supports a wide range of ecosystems, such as fish stocks and other aquatic life, which provide nutrition biomass directly to people (SDG 2: Zero Hunger).

Like green water scarcity, *BW_Scarcity* is defined as the ratio of Blue water footprint (WF_b) to blue water availability, and it highlights mismatches between water availability and water demand (Hoekstra et al., 2011). In general, *BW_scarcity* is represented in percentage, where *BW_Scarcity* = 100% refers to the situation where blue water availability is fully consumed.

For a river basin '*x*' and period '*t*',

$$BW\_Scarcity(x,t) = \frac{Blue\ Water\ Footprint(x,t)}{Blue\ Water\ Availability(x,t)} \tag{3}$$

$$Blue\ Water\ Availability(x,t) = TRWR - EFR \tag{4}$$

Here, the total renewable water resource (TRWR) is the total streamflow available. Quantifying *BW_Scarcity* is essential for food security, ecological health, and economic and business prospects (Nouri et al., 2019; Rosa et al., 2020). The *BW_Scarcity* of a region can be classified into four levels (Hoekstra et al., 2012):

(i) low blue water scarcity: *BW_Scarcity* < 100%, where the WF_b does not exceed the blue water availability, and the EFR is satisfied at this level.
(ii) Moderate blue water scarcity: *BW_Scarcity* ranges from 100 to 150%. Here the WF_b is between 20 and 30% of natural runoff, and the EFR criteria are not satisfied in moderate bluewater scarcity.
(iii) significant blue water scarcity: *BW_scarcity* ranges from 150 to 200%. Here the WF_b is between 30 and 40% of natural runoff. The EFR is not satisfied.
(iv) Severe blue water scarcity: *BW_Scarcity* > 200%. The monthly WF_b exceeds 40% of natural runoff, and the concept of EFR is drastically unsatisfactory in the regions with severe blue water scarcity.

Various studies have assessed the spatiotemporal fluxes in *BW_Scarcity* from a regional to global scale. For instance, Mekonnen and Hoekstra (2016) evaluated the global *BW_Scarcity* at a high spatial resolution (i.e., grid cells of 30 × 30 arc min) on a monthly basis. The result shows that two-thirds of the global population lives under severe water scarcity at least one month each year, and the most severe hot spots identified were India and China. The study also states that a previous study performed on a river basin scale (Hoekstra et al., 2012) underestimated *BW_Scarcity*, thereby increasing the number of people facing water scarcity threats. Water scarcity assessments on an annual basis hide the variability within a year and underestimate the areal extend of severity (Wada et al., 2011; Mekonnen and Hoekstra, 2016). However, the availability of seasonal or monthly scale actual water use data constrains the monthly/seasonal scale analysis of *BW_Scarcity*.

Excluding EFR is another concern in *BW_Scarcity* assessment. For example, Wada et al. (2011) studied global water scarcity at a high spatial resolution on a monthly basis without accounting for EFR and underestimated the number of people facing water scarcity (Mekonnen and Hoekstra, 2016). Certain studies quantified water scarcity by considering the actual runoff and water withdrawal that will lead to the addition of uncertainty in water scarcity levels (Kummu et al., 2014; Oki and Kanae, 2006a,b). The choice of scale is a critical element that affects the outcome drawn from water scarcity analyses (Brunner et al., 2019). Water scarcity may be over or underestimated when the scale changes from local to continental scale.

5. Application of hydrological models for water security assessment

Several modeling approaches have been proposed to quantify water security on a global to local scale (Wada et al., 2011; Rodrigues et al., 2014; Mekonnen and Hoekstra, 2016; Veettil and Mishra, 2016, 2020; Ma et al., 2020). This section reviews the different hydrological and agricultural systems modeling frameworks applied to quantify blue/green/grey water footprint, water availability, and related scarcity.

Although a wide variety of hydrological models are available for simulating the historical and future water availability, selecting a particular model is challenging because of model prediction uncertainty associated with input variables (e.g., land use and climate), model parameter calibration, and scale issues in watershed modeling (Surfleet et al., 2012; Wada et al., 2017). However, process-based, spatially distributed models are capable of evaluating the hydrological or nutrient fluxes in a watershed (Veettil et al., 2021) at various scales. In addition, these models can simulate streamflow and nutrient loads at interior ungauged sub-catchments.

Several studies have applied physically distributed modeling systems to quantify the water footprint, water availability, and related water scarcity. Implementation of a hydrological modeling framework to quantify blue and green water footprints, availabilities, and scarcities based on the simulated hydrologic and nutrient fluxes is illustrated in Fig. 2. The basic spatial and temporal datasets to simulate these variables include digital elevation models (DEM), which provide the topography and hydrography of the region, land use maps, soil information, daily weather inputs, and crop management information. Generally, streamflow and water quality data are needed for model calibration and evaluation. The application of modeling frameworks such as SWAT, VIC, and AgES for water security assessment is explained in further sections.

5.1. Soil and water assessment tool (SWAT)

SWAT is a physically-based, continuous-time, semi-distributed model developed by the United States Department of Agriculture (USDA, Arnold et al., 1998), which has been widely used for simulating the water quantity and quality for a small-scale watershed (Cibin et al., 2012), large river basins (Veettil and Mishra, 2016), to continental scales (Abbaspour et al., 2015). Recently, the model has been applied for water security assessment at a regional scale. Rodrigues et al. (2014) applied SWAT to estimate the blue/green water availability and related water scarcity over an agricultural basin in Brazil. Subsequently, Veettil and Mishra (2016, 2018) used SWAT to quantify the blue and green water scarcity across the counties located in the Savannah River Basin, a transboundary river basin located in the semi-humid eastern US.

The water balance components in SWAT are associated with blue or green water, and the blue water is estimated by combining the water yield and groundwater storage (Rodrigues et al., 2014; Veettil and Mishra, 2016, 2018). Here, water yield refers to the return flow from each HRU (Hydrologic Response Unit, the smallest spatial unit) contributing to streamflow. The groundwater storage is the difference between the total recharge to the deep aquifer and the shallow aquifer contributing to streamflow. Green water storage is the soil water content available for plant consumption, and the green water footprint is the evapotranspiration.

Veettil and Mishra (2016) applied SWAT to quantify the blue and green water availability and green water footprint over the Savannah River Basin. Here blue water footprint is calculated from the USGS water withdrawal data. The result provided an overview of the spatiotemporal changes in county-level water security due to sectoral water demand and shortage of supply in the Savannah River Basin. The potential influence of climate and land-use variables on blue and green water and related water scarcity was also analyzed for the Savannah River Basin using SWAT (Veettil and Mishra, 2018).

SWAT has also been applied to quantify the blue and green water availability of arid regions. For instance, Abbaspour et al. (2009) assessed the impact of climate change on Iran's blue and green water resources. In addition, Schuol et al. (2008) used SWAT to quantify the water availability of African river basins. The information from these models is important because most of the subbasins in those regions are ungauged, and the data on reservoir management, land use management, and agricultural practices are limited. SWAT was also used to evaluate the regional Grey water footprint (WF_y). For instance, Wu et al. (2012) quantified the WF_y due to the biofuel production for the counties

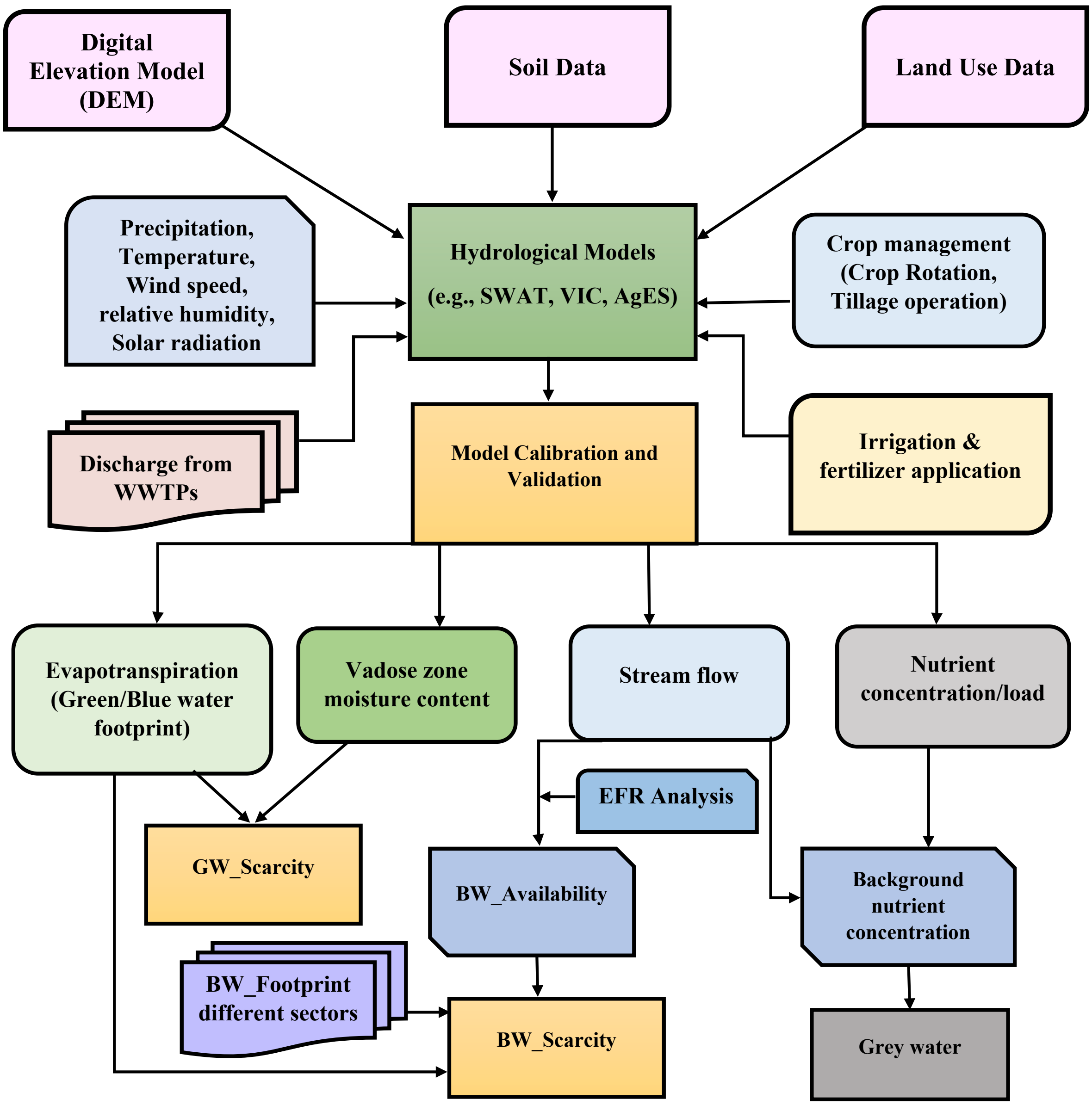

Fig. 2. A basic framework for quantifying blue, green, grey water, and related water scarcity indicators using physically-based hydrological models. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

located in Iowa, and Girolamo et al. (2019) estimated the WFy and its uncertainty for crop production in a basin located in Italy using SWAT.

5.2. Variable Infiltration Capacity (VIC)

VIC is a macroscale hydrological model (Liang et al., 1994, Liang and Xie, 2003) developed to simulate land-atmospheric fluxes, water, and energy balances at independent grid cells. The model routes water as surface and baseflow to the stream network. Veettil and Mishra (2020) used the VIC output to quantify blue and green water scarcity across the CONUS. Here VIC (version-4.0.3) output was obtained from the Giovanni database, which provides the modeled outputs of the North American Land Data Assimilation System (NLDAS) (Rui and Mocko, 2013). The model output is available at a $1/8^0$ grid-scale in near-real-time across the CONUS.

Here, the blue water is quantified by combining the surface runoff and base flow to the stream network, and soil water in the top one-meter soil depth simulated by VIC is considered the green water storage available for plant consumption. In addition, the analysis of *GW_Scarcity* in this study was more realistic by incorporating the rainfed agricultural parcels that avoid blue water resources (irrigation). The results drawn from this study indicate that water security will remain a challenge, particularly in the western USA, due to the compounding impacts of changing climate variables and the growing population. Ma et al. (2020) also utilized the VIC model to report the water scarcity across China, which explicitly investigated water quality requirements for human use.

6. Application of agricultural Ecosystems Services (AgES) model for blue, green, and grey water security assessment

Unlike SWAT and VIC, AgES is a fully distributed watershed model capable of routing water and nutrients among the HRUs (smallest units inside a catchment) and stream units. AgES is a relatively new model, and the current version is continuous in time at a daily time step (Ascough et al., 2012; Green et al., 2014, 2015). The hydrological processes in AgES were initially adapted from the J2000 (Krause et al., 2006) and J2000-SN (Fink et al., 2007) models. The current version 0.3.0 of AgES simulates surface runoff, lateral flow from multiple soil layers, fast discharge from the saturated zone, and slower baseflow from the saturated zone. The soil–water process component is the central part of the model that connects the evapotranspiration, surface, subsurface flow, and groundwater storage. The spatial distribution of precipitation in AgES is estimated by the inverse distance weighting interpolation method. AgES quantifies the interception storage from precipitation at each HRU based on the land use pattern and vegetation (leaf area). Currently, the model incorporates two alternative methods of soil infiltration: Eagleson method (Eagleson, 1970) and curve number method (Coleman et al. 2016). In this section, we present an application of AgES to estimate blue, green, and grey water across an intensively managed watershed located in the semiarid USA.

The major consumption or footprint of crops is quantified as ET. Calculating WF_g based on the model output for a rainfed agricultural field is readily accessible because the blue water resources do not influence it. In irrigated crops, differentiating the amount of ET from green water (i.e., rainfall) and blue water (i.e., irrigation) is challenging. After running the model with selected irrigation options (e.g., surface or sprinkler irrigation), one can calculate the total water evapotranspired during the crop growing season from the model output. One widely practiced method to quantify the blue water ET (WF_b) is calculating the difference between total water evapotranspired and ET during the rainfed conditions (WF_g) (e.g., Mekonnen and Hoekstra, 2010, 2011; Hoogeveen et al., 2015). In this study, we followed this method for quantifying the WF_g and WF_b across the irrigated fields. However, irrigation and precipitation water mix in the root zone before being transpired, and rooting depth under rainfed and irrigated conditions may differ and affect the water uptake by plants. Therefore, this approach may overestimate or underestimate the spatiotemporal distribution of ET across the watershed.

Simulating the crop rooting depth (Hoekstra, 2019a,b) and estimating moisture supply (green water storage) in the root zone often remain uncertain in research (Mishra et al., 2015). Therefore, we considered the top two soil layers for quantifying green water storage (soil horizon depth considered in the study is based on SSURGO soil data, where the average soil depth = 70 cm). The total blue water is calculated as the sum of surface and subsurface flow from the calibrated AgES model. Our study also considered the WF_y produced due to crop management practices and wastewater treatment plants (WWTPs). The WF_y (nitrate) for the BDCW is calculated using Eq. (1), where the natural nitrate concentration is derived from the national atmospheric deposition program.

6.1. Study area description and data

The Big Dry Creek Watershed (BDCW, area = 280 km^2) is an intensively managed, mixed agri-cultural and suburban watershed located in the semiarid region of eastern Colorado, USA (Fig. 3). Most of the precipitation in the watershed occurs as rainfall in the summer, and the annual average precipitation in the watershed is 315 mm. The headwater area of BDCW is Rocky Flats, which consists of grassland. The watershed is substantially influenced by the Standley Lake reservoir located in the upper basin, which supplies water to the downstream agricultural land, and by discharges from the three major domestic wastewater treatment plants (WWTPs: Broomfield, Westminster, and Northglenn), diversion structures, irrigated and non-irrigated agricultural fields. The central portion of the watershed is comprised of mostly suburban land, which is a mixture of residential, commercial, and industrial areas. The lower watershed is focused on agricultural activities, including corn, alfalfa, winter wheat, and pastureland (Veettil et al., 2021).

Inflows to Big Dry Creek from Standley Reservoir and three WWTPs provide continuous baseflow and nutrient loads. These ’inlet flows’ play critical roles in controlling the blue and grey water components in the BDCW. Various spatiotemporal input data to run the AgES model and the sources obtained are provided in Table 3.

The upper watershed area, including Standley Reservoir and Rocky Flats, is not directly modeled in our analysis. The USGS (06720820)

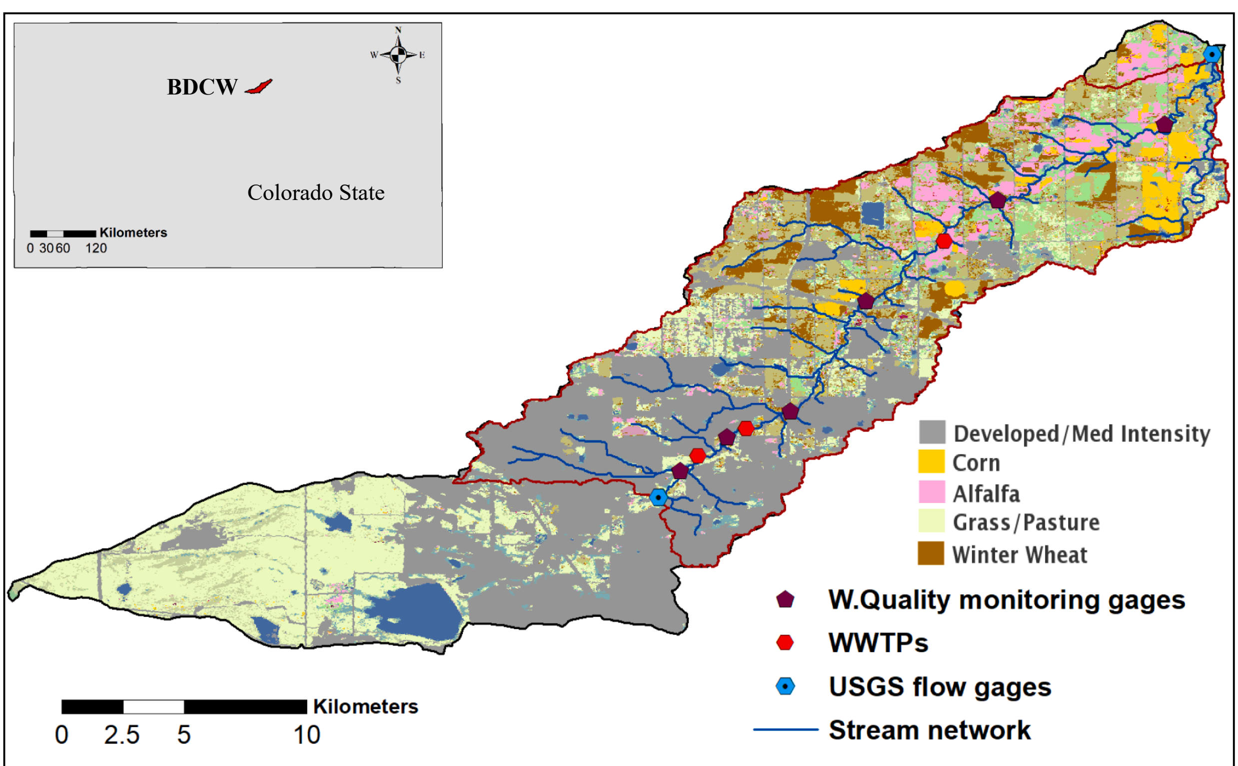

Fig. 3. Spatial location of the Big Dry Creek Watershed (BDCW) and major land use and crops. The red line shows the lower watershed area considered in the analysis. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Input data use for AgES model development (Veettil et al., 2021).

Data used	Description	Resolution	Source and Reference
Topography	Digital Elevation Model (DEM)	10 × 10	NED, USGS (NED, 2002)
Land use map	Crop Data Layer	30 × 30	USDA (NASS CDL, 2018)
Soil map	The SSURGO data base provides detailed information of soil classes	1:12,000 to 1:63,360	USDA (NRCS, 2012)
Temperature	Maximum, minimum, and mean daily air temperature	Daily	NCDC, CDSS, COAgMET
Precipitation, Relative humidity, solar radiation, wind speed	Daily mean for each variable and station	Daily	Iowa Environmental Mesonet (IEM) and CoAgMet (Open data, 2019)
Wastewater treatment plant (WWTP) effluent discharge	Three major WWTPs discharge into the watershed stream network	Daily	Big Dry Creek Watershed Association
Streamflow Gages	Inflow and outflow	Daily mean	USGS

discharge gage located downstream of Standley reservoir is considered the upstream inlet point of BDCW. The location of BDCW and the area considered for direct modeling are illustrated in Fig. 3. The delineation was performed using a web-based watershed delineation tool called the *Catchment area delineation* (Cadel) tool, which delineates watershed boundaries, sub-catchments, spatially explicit HRUs (each HRU has spatial reference and geospatial attribute table), and stream network inside each sub-catchment (https://alm.engr.colostate.edu/cb/wiki/42641). Here, the HRUs in the cropland are delineated by preserving the boundaries of irrigated crop fields. This method facilitates the simulation of spatially explicit crop management practices (e.g., irrigation, fertilizer application) in the fields. The final Cadel result generated 1551 HRUs distributed over 16 sub-catchments. The crop management practices, especially in the irrigated fields, were identified using the Land-use and Agricultural Management Practices web-Service (LAMPS, Kipka et al., 2016). A detailed explanation of this AgES model project development is provided by Veettil et al. (2021).

In this study, the Eagleson (1970) method quantifies the infiltration amount to the soil profile, which depends on the soil characteristics such as hydraulic conductivity, field capacity, and soil porosity. Crop management practices in a watershed have a substantial role in managing the three components of the total water footprint (WF_g, WF_b, and WF_y). However, we do not have a perfect record of crop management practices in the watershed. Based on the application of LAMPS, the major crops in the watershed are identified as corn, alfalfa, winter wheat, and pasture.

Like SWAT, AgES provides an option for auto-irrigation, which works based on the water content available in the Medium Pore Storage (MPS) below field capacity. Whenever the water content in the MPS falls below a threshold (set by the user), the model will apply irrigation to the field. The total seasonal irrigation amount required for each crop (i.e., input irrigation amount) and fertilizer application rates in the region were obtained from Colorado State University Extension (Schneekloth and Andales, 2017).

Model Performance Evaluation: The stream flow and nitrate flow in the BDCW was calibrated using LUCA (Let Us Calibrate; Hay and Umemoto, 2007), a multi-objective, stepwise, and automated calibration tool that works based on Shuffled Complex Evolution (SCE) algorithm (Duan et al., 1994). The stream flow is calibrated against a USGS flow gaging station located in the watershed outlet, and the nitrate concentration is calibrated for six water quality gaging stations (obtained from the Big Dry Creek Watershed Association) located in the interior watershed.

Finally, the model calibration was performed at a daily scale for 2012–2018 using the Kling Gupta Efficiency (KGE, Gupta et al., 2009) as an objective function and tested for 2010 and 2011, years with greater uncertainty of the inputs from WWTPs. Performance of the model was further evaluated using the percent bias (PBIAS), coefficient of determination (R^2), and Nash-Sutcliffe Efficiency (NSE). In the case of streamflow calibration, the daily model simulation results show very good agreement with observed USGS flow at the watershed outlet. For instance, the calibrated KGE value was 0.88, and the NSE was 0.77. The values of daily and monthly model performance of AgES for the streamflow simulation are PBIAS (0.68 %), R^2 (0.78), NSE (0.77), and KGE (0.88) based on the 2012–2018 period (Veettil et al., 2021). In addition, AgES was able to represent the nutrient fluxes in the interior watershed adeptly (Table 4).

6.2. Spatial distribution of blue and green water

Hydrological components, such as surface water flow, interflow, and groundwater flow from the calibrated AgES, were used to calculate the blue water across the HRUs of BDCW. Each "flow" is computed as the net flux from an HRU to an adjacent HRU and a stream reach. Deep percolation recharges groundwater and may also be considered a part of the net groundwater return flow. The spatial distribution of mean annual blue water across the HRUs of BDCW for the model calibration period (2012–2018) is illustrated in Fig. 4a. The spatial distribution of blue water was found to be influenced by the rainfall and land use pattern of the watershed (Veettil and Mishra, 2018; Karabulut et al., 2016). The upper watershed area receives a relatively higher amount of annual precipitation, where the HRUs showed higher values of blue water ranging from 100 mm to more than 500 mm. The major land use pattern of the upper watershed area is urban, which generates a higher amount of surface water return flow. The average blue water at the lower watershed area, where most irrigated agricultural fields are located, is drastically lower than the upper watershed area. However, the groundwater return flow and the lateral flow at these HRUs were higher than the HRUs in the upper watershed, which indicates that the surface water return flows highly influences the blue water resources in the BDCW.

The spatial distribution of green water storage across the BDCW is illustrated in Fig. 4b. Unlike blue water, green water storage showed relatively less variation throughout the BDCW. The maximum green water storage was observed in the central part of the watershed, where the precipitation is also high. Here, the green water storage is quantified by neglecting the irrigation application in the BDCW because green water storage is the soil moisture available from the precipitation. Therefore, considering the irrigation amount in green water storage calculation will lead to inaccurate (over) estimation of green water storage (Veettil and Mishra, 2020; Hoekstra et al., 2011). The lower watershed area showed comparatively less green water storage ranging from 200 mm to 350 mm. Most of the lower watershed area is comprised of loess soils with relatively high infiltration capacities. Therefore, a relatively low rainfall will lead to lower green water storage in these

Table 4
Goodness of fit statistics between models simulated nitrate (daily concentration) with measured nitrate amount in the BDCW water quality monitoring gages (2012–2018) (Veettil et al., 2021).

Monitoring Gages	Goodness of fit statistics			
	PBIAS (%)	R^2	NSE	KGE
BDC 1.5	−1.4	0.84	0.80	0.84
BDC 2	−7.6	0.71	0.62	0.80
BDC 3	−8.5	0.8	0.71	0.84
BDC 4	15.6	0.64	0.34	0.74
BDC 5	18.6	0.51	0.18	0.65
BDC 6	−4.5	0.38	−0.57	0.31

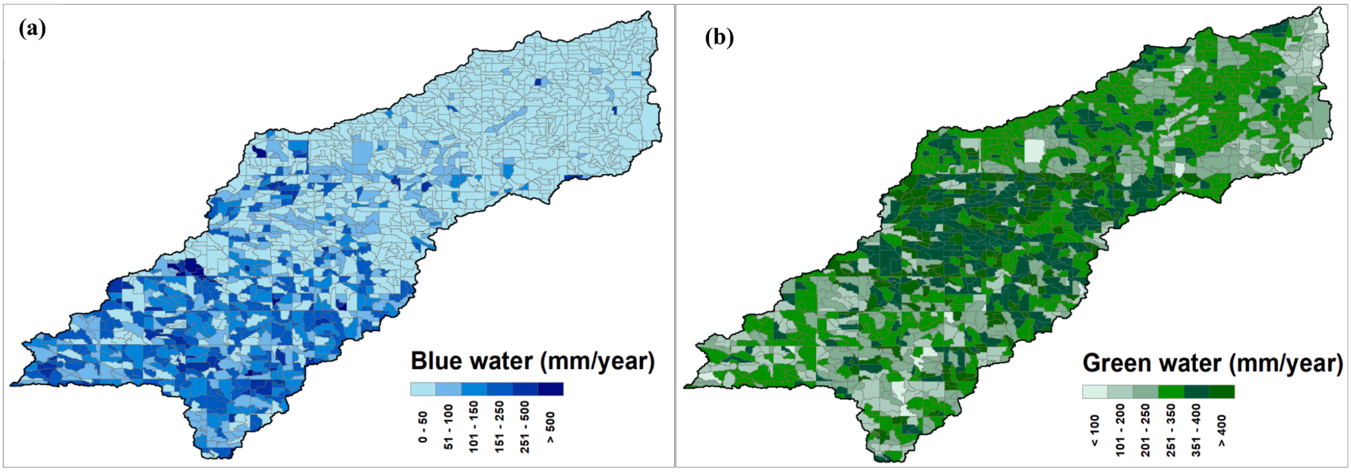

Fig. 4. Spatial distribution of mean annual (a) blue water and (b) green water storage over the HRUs of Big Dry Creek watershed. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

HRUs. Conservation practices such as residue management and practicing no-till agriculture may improve the amount of green water storage in the lower part of BDCW. The analysis of green water storage indicates that the lower BDCW may not be capable of practicing rainfed agriculture. Therefore, enormous blue water resources (irrigation applications) are required to optimize crop yield.

6.3. Spatial distribution of blue, green, and grey water footprint

Identifying the sources (blue (i.e., irrigation) or green water (i.e., rainfall)) of plant water consumption is important, particularly in water-scarce regions. The WF_b and WF_g calculated from the irrigated agricultural fields of BDCW are illustrated in Fig. 5a and 5b, respectively. It is observed that the WF_b from most of the irrigated agricultural fields is

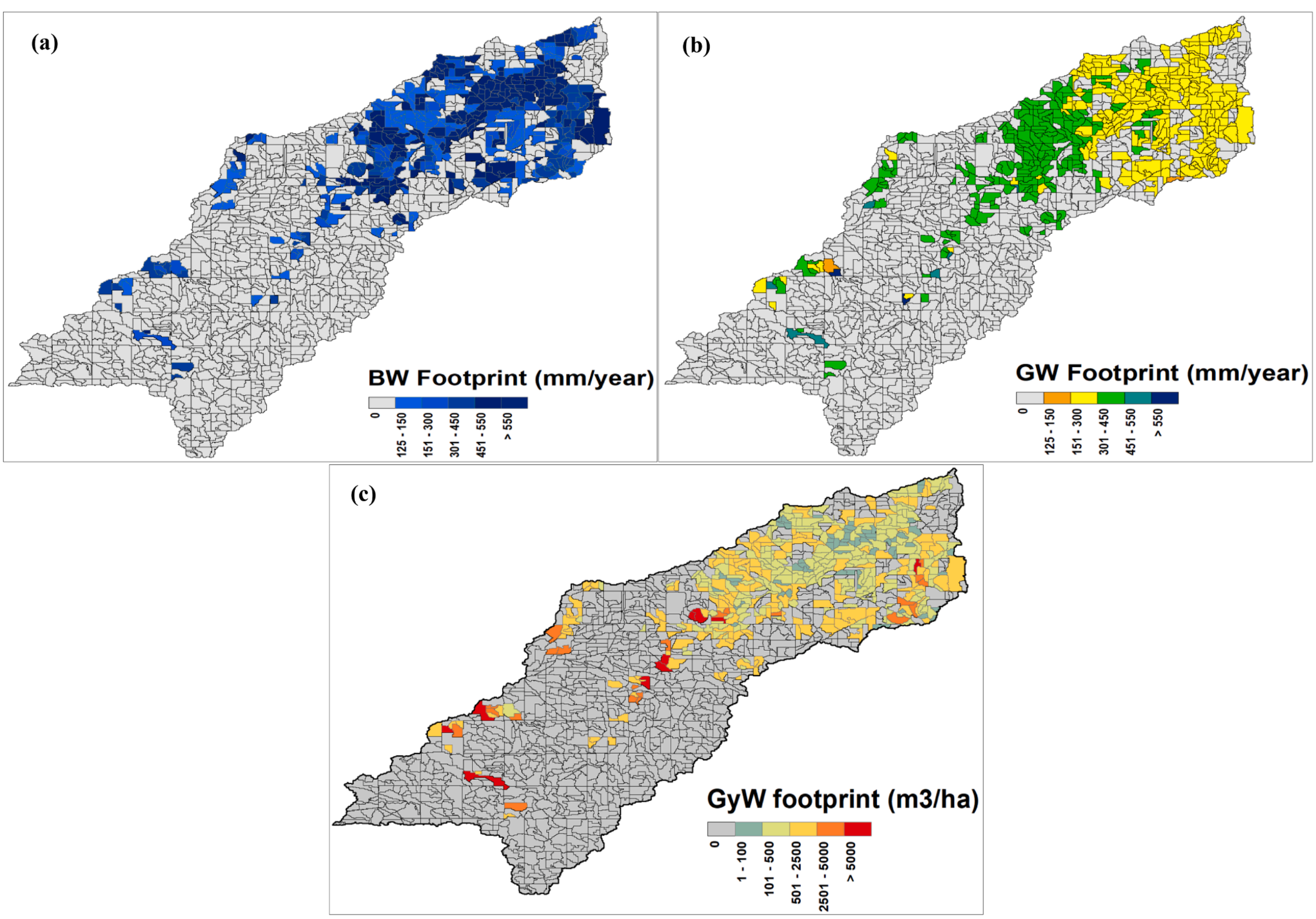

Fig. 5. Spatial distribution of mean annual (a) blue, (b) green, and (c) grey water footprint over the irrigated agricultural fields of Big Dry Creek watershed. The grey water footprint is estimated in cubic meters per hector (m^3/ha). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

relatively higher than the WF_g. In particular, alfalfa showed a maximum WF_b (450 mm to 550 mm), and winter wheat showed a lesser WF_b, whereas the WF_g in most fields varied from 150 mm to 450 mm. It is also important that in a semiarid region, most irrigation goes to ET. Therefore, in general, WF_b is higher than WF_g in semiarid watersheds.

The total WF_b observed during 2012–2018 was 28 km^3/year, which was nine percent greater than the total WF_g quantified for the BDCW. As mentioned, alfalfa takes the largest share in the WF_b, 54% of total WF_b followed by hay/pasture (21%). In the case of WF_g, the alfalfa contributed only 30% to the total WF_g. Whereas, winter wheat showed a higher WF_g, which contributes 41% of the total WF_g. According to the Colorado State University Extension department (Schneekloth and Andales, 2017), winter wheat's estimated seasonal water requirement is less than other crops, and a major portion is received from effective precipitation over the basin. The seasonal water requirement for alfalfa and pasture is higher than other major crops in the watershed, which is provided as supplemental irrigation. Overall, the total water requirement (WF_b + WF_g) of the major crops in the BDCW is 53.75 km^3/year, where most of the blue water is consumed by alfalfa, and winter wheat consumes primarily green water.

In this study, we considered the crop management practices (fertilizer application) and the inflow from the WWTPs as the sources of WF_y in the BDCW. The spatial distribution of WF_y across irrigated agricultural fields is illustrated in Fig. 5c. A higher amount of WF_y in the BDCW is observed in the cornfields. The agronomic application of nitrate fertilizer in the cornfields is higher than the remaining crops. This may be a reason for higher WF_y contribution from the cornfields. Most of the winter wheat fields also showed a higher amount of WF_y. However, not unexpectedly, spatial variation of grey water does not follow the spatial pattern of green water or blue water since it also considers the natural background concentration of the stream network. Overall, the results show that grey water is highly associated with the fertilizer application rate, and the variation of WF_y is much higher than WF_b and WF_g for BDCW.

7. Other models

Physically distributed hydrological models are useful for quantifying blue water, green water storage, and WF_g. The aforementioned hydrological models may not evaluate the WF_b in different sectors, such as thermoelectric power generation, mining, and industry. However, these models can be applied for calculating the WF_b from irrigation water use. In addition, several studies have applied CROPWAT to quantify WF from various agricultural crops (Chapagain and Hoekstra, 2011; Chapagain and Hoekstra, 2007; Gerbens-Leenes et al., 2009; Kongboon and Sampattagul, 2012; Mekonnen and Hoekstra, 2011). Like SWAT and AgES, a user can specify input irrigation scheduling options in CROPWAT. There are many ways to model ET and crop growth, including the EPIC crop modeling framework (Williams et al., 1989; Williams, 1995), also available in grid-based form (GEPIC; Liu et al., 2007), and AQUACROP (FAO, 2010). Other models applied for quantifying the crop WF calculation, which depends on water budget equation, are PolyCrop (Nana et al., 2014), Decision Support System for Agrotechnology Transfert – Cropping System Model (DSSAT-CSM; Dalla Marta et al., 2012), and Lund-Potsdam-Jena managed Land (LPJmL; Rost et al., 2008).

8. Discussion and concluding remarks

A proper water security assessment is essential for facilitating the increasing freshwater demand to satisfy human needs and sustain ecosystem health within a watershed. The water security assessment should focus on the managing strategies, such as increasing crop yield by reducing blue water footprint and reducing the stress on blue water resources by focusing on the rainfed agricultural practices. This study reviewed the concept and necessity of water security assessment by focusing on water security indicators. We also reviewed the application of different physically-based hydrological models, such as Soil and Water Assessment Tool (SWAT) and Variable Infiltration Capacity (VIC), on water security assessment. To illustrate the water security assessment based on blue, green, and grey water footprint, a fully distributed Agricultural Ecosystems Service (AgES) model is applied in an intensively managed watershed in the semiarid Colorado State. The following conclusions are drawn from this water security assessment:

(a) Rapidly growing population and associated increases in water demands of different sectors such as agriculture, domestic, municipal, and industrial water usage strongly impacted regional water scarcity. Economic development and dietary shift towards more meat-based products, changing land use, and climate patterns cause stress on blue and green water resources.

(b) Excessive nutrient/pollutant loading from wastewater treatment plants to the stream network and the nutrient flow from highly managed agricultural fields contribute towards water quality deterioration, resulting in water security issues at a regional scale. However, most water security analyses only focus on the water quantity aspect, which will lead to the under-estimation of water security issues in a region. Evaluation of grey water indices for nutrient discharge zones can indicate the degree of water quality degradation of a watershed; therefore, expanding water quality monitoring gauges in a river network is essential to achieving this goal.

(c) The water security assessment often ignores the return flows after consumptive use. Return flows can often be reused and thus do not necessarily contribute to water scarcity. Therefore, water footprint-based analysis that accounts for both water consumption and return flows can provide a comprehensive picture of water scarcity over a watershed.

(d) Several modeling approaches are proposed to quantify water security at local to global scales. Hydrological models, such as Soil and Water Assessment Tool (SWAT) and Variable Infiltration Capacity (VIC), are useful to quantify blue, green water availability and footprints. Hydrological/agricultural system models cannot quantify evapotranspiration from irrigation and rainwater separately. Therefore, independent quantification of blue and green water footprint from the irrigated field is challenging.

(e) We quantified the blue, green, and grey water footprint indicators across a semiarid watershed located in Colorado State by applying the Agricultural Ecosystems Services (AgES) model. The fully distributed nature of AgES allows the user to calculate blue, green, and grey water footprint explicitly from each HRU. The total blue water footprint observed during 2012–2018 was 28 km^3/year, nine percent higher than the total green water footprint in the watershed. Alfalfa consumes the largest share of the blue water footprint (54% of the total WF_b), followed by hay/pasture (21%). In the case of green water footprint, alfalfa contributed only 30% to the total green water footprint. The spatial distribution of grey water footprint is strongly related to fertilizer application, and the variation of grey water footprint across the irrigated parcels was relatively higher than blue and green water footprint.

CRediT authorship contribution statement

Anoop Valiya Veettil: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Validation, Visualization, writing-original draft. **Ashok Mishra:** Conceptualization, Funding Acquisition, Investigation, Methodology, Project Administration, Resources, Supervision, Writing-review and editing. **Timothy R. Green:** Conceptualization, Investigation, Methodology, Project Administration, Resources, Software, Supervision, Writing-review and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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